

Monitoring mangrove association changes in the Can Gio biosphere reserve and implications for management

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ARTICLE INFO

Keywords:

Mangrove associations
Support Vector Machine
SPOT imagery
Can Gio biosphere reserve
Human activities
Object-based image analysis

ABSTRACT

Mangrove forests are useful in protecting coastal lines, reducing atmospheric carbon dioxide (CO₂), and providing shelters and foods for ecosystems, but they are among the top threatened habitats worldwide caused by human activities, climate change, and coastal-related natural disasters such as tsunamis, flood, storm, etc. Understanding quantitative and spatial information of mangrove associations is essential for managing mangrove forests effectively. The main aim of this research is to investigate the changes of mangrove forest associations in tropical regions and possible reasons of changes via the case study of the Can Gio biosphere reserve in Viet Nam by using remote sensing datasets (SPOT 4 and 5 imagery), object-based image analysis and Support Vector Machine classifier. The classification results showed that the highest overall accuracy of this combination was 81.6%, given 420 reference objects, confirming the applicability of using remote sensing on assessing the development of mangrove forests. For the case study, we found that there was a decrease of the *Avicennia alba* – *Sonneratia alba* (Association I) area by 20.1% caused by the development of aquaculture and other human activities, but there was an increase of the *Rhizophora apiculata* (Association II) area by 34.8%. These trends may result in the exacerbated risk of soil erosion and make the region become more vulnerable to climate change and tropical storm events. Management policies should be revised to harmonise the benefits of economic development, environmental protection, and species diversity.

1. Introduction

There is evidence that mangrove forests provide various ecological and economic benefits. In the context of global climate change, mangrove forests are useful in mitigating greenhouse gas emission. Mangroves are proved to be among the most effective trees compared to other terrestrial tree species in absorbing carbon dioxide (CO₂) according to Alongi (2012). Nevertheless, the world is suffering from a considerable replacement of mangrove forests for shrimp farms, salt farms, urbanisation and other human activities (Liu et al., 2014; Valiela et al., 2001). It was reported that a two-third of Viet Nam's mangrove areas, approximately 253,210 ha, was lost over the period 1943–2000 (Sam et al., 2005; Vo et al., 2013). Besides human activities, the existence of mangrove forests is also influenced by natural drivers such as sea level rise. Measured data analysis showed that sea level rise has

threatened coastal regions of the Mekong Delta and its neighbouring regions with a rate of 4 cm per year over the last decade (Dang et al., 2016). This phenomenon has a negative influence on mangrove forests such as reducing their viability and the quality of their ecological and economic functions and services which consequently leading to environmental and ecological problems.

Although the state government of Viet Nam has recently invested into projects in mangrove forest plantation and conservation to confront the effect of climate change - sea level rise and tropical typhoons on coastal erosions, the lack of information about the quantitative and spatial distribution of mangrove forests in Viet Nam hindered their efforts (Pham and Yoshino, 2016). To manage mangrove forests better, information about mangrove associations plays a crucial role; where to restore and which species should be planted are some of the questions that managers are used to ask. In addition, monitoring mangrove

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<https://doi.org/10.1016/j.rsase.2018.11.009>

Received 6 June 2018; Received in revised form 25 October 2018; Accepted 20 November 2018

Available online 23 November 2018

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quality by detecting different species is important because this information can be used to evaluate the status of biodiversity.

Approaches for mangrove mapping applied in the country have showed different accuracies and inconsistent results (Kuenzer et al., 2011). Therefore, applying state-of-the-art approaches for mangrove mapping is essential to provide accurate mangrove information for effective mangrove management, climate change mitigation, and the implementation of payment of ecosystem services strategies. In general, there are two main approaches for mapping vegetation: field survey and remote sensing data analysis (Adam et al., 2010). Although the field survey method is more accurate, it is costly, time-consuming, and labour-intensive, especially for large areas (Adam et al., 2010). Remote sensing, which can provide data of distant regions and provide considerable spatial and temporal coverage, can be used as an alternative source for mapping vegetation (Dang et al., 2018b; Adam et al., 2010).

The application of remote sensing for mangrove type classification in Viet Nam has been documented in the literature. Previous studies have used the pixel-based approach for mapping mangrove types in Viet Nam such as Luong et al. (2015); Thu and Populus (2007); Hauser et al. (2017) and Pham et al. (2018). Nevertheless, due to misregistration or the problems of cloud coverage and cloud shadow, the pixel-based classification approach may result in noisy outputs. The newly developed object-based image approach (OBIA) has advantages over the pixel-based approach because it reduces mapping uncertainties by merging pixels with similar characteristics (Blaschke et al., 2014; Han et al., 2014; Lee et al., 2016). In addition, OBIA not only uses spectral information but also spatial and contextual characteristics into classification processes to perform classification more accurately (Han et al., 2014; Lee et al., 2016; Pham et al., 2016). It also helps to identify multi-scale objects from a single image or across many images (Kamal et al., 2015).

The objects derived from satellite images can be classified by either parametric or non-parametric classifiers. The non-parametric classifiers produce better prediction because sampling data does not have to follow any probability distribution (Lu and Weng, 2007) which is the case of feature data of mangrove forests. Among non-parametric classifiers, we chose the Support Vector Machine (SVM) classifier because this is a robust and optimal margin-based classification technique. Additionally, this technique is often used when the numbers of features are comparably high to the numbers of reference objects.

In this study, we hypothesized that current human activities along the coast and rivers caused the loss of riparian and coastal species while the effort of the government in mangrove forest rehabilitation would reserve the total area of mangrove; climate change – sea level rise, however, will pose more pressure on the preservation of mangrove forests in the future. To evaluate this hypothesis, this research examines the possibility in applying OBIA and SVM for mapping mangrove associations in the Can Gio forest, identifies temporal and spatial changes of mangrove forest associations based on the classification efforts, and predicts reasons behind any changes.

2. Materials

2.1. Study area

The mangrove forest in Can Gio (10°22'14" – 10°40'09" N; 106°46'12" – 107°00'59" E), which was recognised as the first biosphere reserve in Viet Nam by UNESCO in the year 2000, is an important wetland in the southeast region of Ho Chi Minh City (HCMC) – a key economic centre in Viet Nam (see Fig. 1). Covering an area of over 75,000 ha, this region has high biodiversity with about 250 species of fauna and flora dominated by mangrove (Tuan et al., 2002; Tuan and Kuenzer, 2012a). Three main flora associations were considered in this study: *Avicennia alba* – *Sonneratia alba* (Association I), *Rhizophora apiculata* (Association II) and remaining type (Association III or Mixed species) (Pham and Brabyn, 2017; Tuan et al., 2002). The first

association is often found along estuaries, riverbanks, and watery, muddy flats. This association can be tolerant under high salinity conditions and can grow on unstable soil (Tuan et al., 2002). The second association locates on stable lands and covers a large area of the Can Gio mangrove forest. The third association is on higher grounds and stable clay, and includes species such as *Phoenix paludosa*, *Ceriops zippeliana*, and *Lumnitzera racemosa* (Tuan et al., 2002).

In the extent of this study, classifying mangrove species was carried out at the association level with dominant species. This approach is appropriate to apply to large areas like Can Gio because more detailed classifications require very high spatial resolution images and costly to achieve.

2.2. Field data collection

The stratification method was used to divide the study region into small groups (or strata). This process was implemented based on a status map, provided by the HCMC Forest Protection Department, which had land cover types such as *Rhizophora apiculata*, mixed mangrove, *Avicennia alba* – *Sonneratia alba*, bare lands, rivers, and muddy flats. A total of 420 reference objects was collected during field trips in Can Gio in 2000 and 2011 (Fig. 1), including mangrove associations and their GPS coordinates.

2.3. Image data

In this study, we used SPOT imagery because it was available and cost-effective data compared to using other aerial imagery. Two images (SPOT 4 and SPOT 5) captured on 10:43 26th March 2000 and 10:40 24th February 2011 (UTM 48P) which had a 10 m spatial resolution and four multispectral bands, were acquired for this research. The multispectral bands include green (500–590 nm), red (610–680 nm), near-infrared (NIR, 780–890 nm), and mid-infrared (MIR, 1580–1750 nm). These images with the same resolution were used for the purpose of comparing vegetation cover changes overtime and accuracy assessment of classified images. The year 2000 was chosen because it marked the declaration of the Biosphere Reserve for the Can Gio mangrove forest by UNESCO. The year 2011 was selected because it helped us to understand what happened after 11 years as it normally takes 10–15 years for a mangrove tree to reach maturity. In addition, Digital Elevation Models (DEMs) in 2000 and 2010 with a resolution of 20 × 20 m provided by Geomatics Centre, Viet Nam were used to support classification processes.

3. Methodology

The mapping procedure with Object-Based Image Analysis (OBIA) included three following steps. Firstly, the SPOT images were processed for geometric and atmospheric corrections. Secondly, the pre-processed images were segmented with OBIA to create objects. Correlation-based feature selection was employed for choosing useful features. Finally, we used Support Vector Machine, a machine learning technique, for classification. Fig. 2 provides an overview of the method developed and a detailed description and justification of the three main steps is discussed further in the following sections.

3.1. Image pre-processing

The pre-processing process included three steps to minimize the discrimination of the multi-temporal images. Firstly, the SPOT images were projected based on the topographic maps of HCMC with a scale of 1:5,000 (Data source: DONRE, 2010) using the first order polynomial transformation and nearest neighbour resampling algorithm. By using this resampling method, the values of original pixels of the images could be maintained (Neteler, 2010). Secondly, radiance values of the images were calculated from digital numbers (DNs) using the following

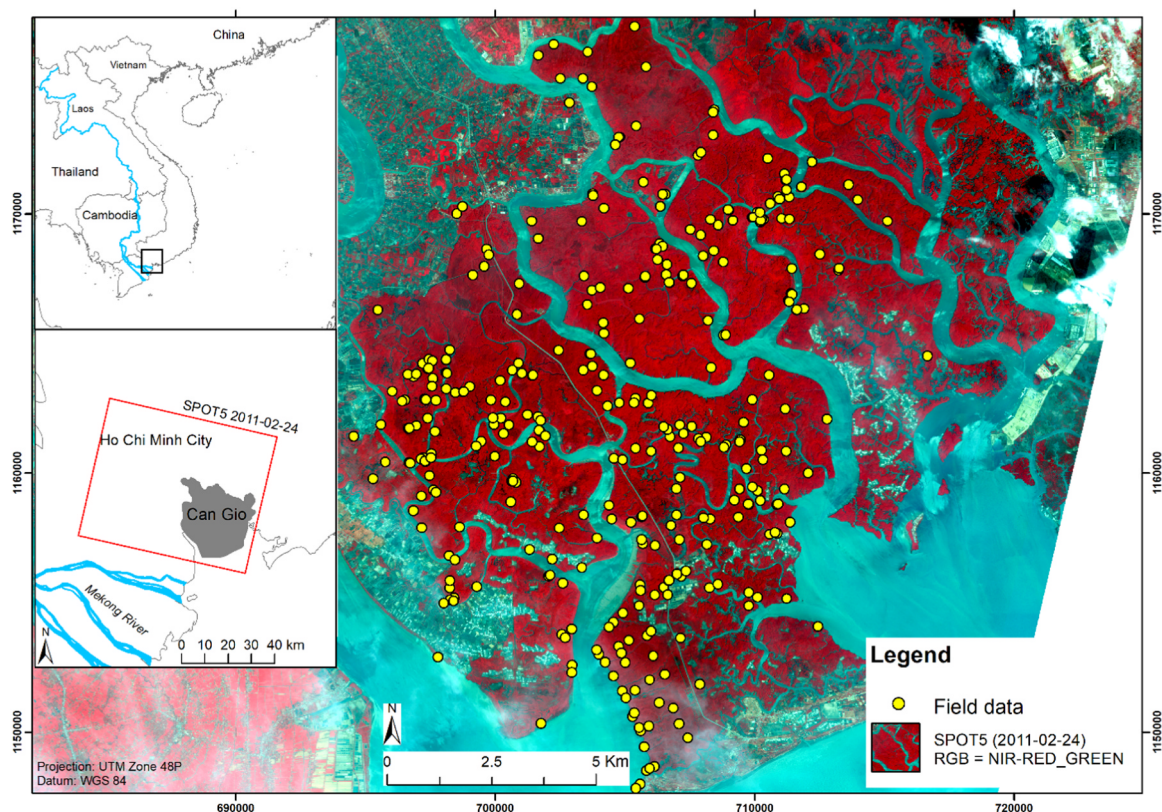


Fig. 1. SPOT5 image of the Can Gio study area and field data (WGS 1984 UTM 48P).

equation (Clark et al., 2011):

$$L = (DN/A) + B \quad (1)$$

Where: L: spectral radiance at aperture sensor ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$); DN: digital number; A: absolute calibration gain for the considered spectral band; B: absolute calibration offset for the considered spectral band. Subsequently, atmospheric correction was carried out to obtain surface reflectance using FLAASH in ENVI, with the atmospheric visibility collected from the National Centre for Hydro-Meteorological Forecasting, Viet Nam (atmospheric model = tropical, aerosol model =

rural, and CO_2 mixing ratio = 390 ppm).

3.2. Image segmentation

The biosphere reserve is a heterogeneous site with water bodies (rivers, channels and ponds), non-vegetation (bare lands and roads) and vegetation. Thus, we need to identify and extract vegetation objects prior to classifying the mangrove associations. The object-based image analysis could provide a higher level of accuracy than the pixel-based approach in mangrove mapping (Kamal and Phinn, 2011); therefore, it

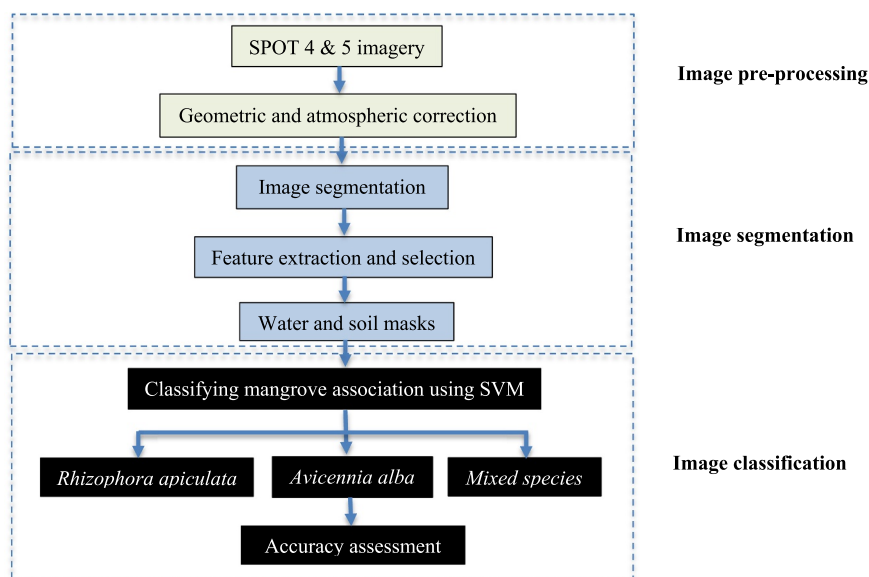


Fig. 2. A workflow of mangrove association classification from satellite imagery.

was chosen in this research. The segmentation process started with single pixels; the pixels were then merged with neighbours based on their spectral and shape information to create larger objects (Trimble Germany GmbH, 2015). As a result, the segmented objects would provide more information for vegetation classification. The four bands from the SPOT imagery were used as input layers for segmentation processes with higher weights to the NIR band than others.

After image segmentation, water objects were masked from other features. Objects were classified as water if the mean of Normalized Difference Water Index (NDWI) was higher than zero and the mean of Normalized Difference Vegetation Index (NDVI) was less than 0.3 (McFeeters, 1996). These parameters and thresholds were applied to this study area because object spectral reflectance responses between images varies (Kamal et al., 2015). NDWI was calculated by using the GREEN and Near-Infrared (NIR) wavelengths when the spectral reflectance of the RED and NIR bands was used to calculate NDVI as following:

$$NDWI = \frac{(GREEN - NIR)}{(GREEN + NIR)} \quad (2)$$

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (3)$$

These water objects included both river and shrimp pond objects. We further distinguished river and shrimp pond objects based on the length threshold of water objects (2 km). Identifying rivers was necessary so that the distance between vegetation and rivers could be calculated. This distance information was a useful input for improving the classification of different vegetation associations. For example, Type I could be found near the river while others located further (Fig. 3).

The remaining objects were non-water, including non-vegetation and vegetation objects. To separate vegetation from non-vegetation objects, objects with the NDVI values higher than 0.3 were assigned as vegetation objects.

3.3. Mangrove association classification

The four spectral bands of SPOT 4 and SPOT 5 and DEMs were used for segmenting vegetation objects. Besides spectral information, topographic data was added for segmenting to increase the accuracy of the vegetation classification step (Kim et al., 2010). The weight for each input layer was set at one (1), and the weight for the NIR band was set at four (4) since vegetation reflectance was more sensitive in the NIR band (Johnson and Xie, 2011).

There were 52 features used for classification, including mean, standard deviation and texture variables of spectral (GREEN, RED, NIR, and MIR) and topographic data (DEM, Aspect, Slope, and Distance to rivers) (see Table 2). Apart from the topographic variables, which were

calculated in ArcGIS, the eCognition 9.1 software package was employed to generate the other features from the SPOT 4 and SPOT 5 imagery. The texture features were calculated using Haralick's algorithms, which included Grey-Level Co-occurrence (GLCM) and Grey-Level Difference Vector features (GLDV).

Correlation-based feature selection (CFS), a multivariate filter algorithm, was used to select features for classification. CFS was implemented using the WEKA data mining package (Witten et al., 2016). This method was chosen because it is computationally cheap and operated independently of the choice of classifiers (Galelli et al., 2014). The CFS's feature subset evaluation function is described in details by Hall (Hall, 1999).

Support Vector Machine (SVM) with Gaussian Radial Basis Function (RBF) was used for this study. C (cost parameter) and γ were the two parameters used for the RBF kernel. The theory of SVM was developed by Vapnik (1995). The goal of SVM is to define an optimal hyperplane which has the largest distance from the nearest training data points of any class. The distance between the separating hyperplane and the closest training data points is called the margin. Given the training data T with n samples: $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, $x_i \in R^d$ and $y_i \in \{-1, 1\}$, $i = 1, 2, \dots, n$, the SVM classification model can be written as:

$$f(x) = \text{sign} \left(\sum_{i,j=1}^n \alpha_i y_i K(x_i, x_j) + b \right) \quad (4)$$

where K is the kernel function, α_i is a Lagrange multiplier, and b is a scalar bias term.

Producer accuracy (PA), user accuracy (UA), overall accuracy (OA), and similarity index (Mean_{SIM_Size}) were the metrics used to measure the accuracy of each classifier (Kamal and Johansen, 2017; Whiteside et al., 2012; Zhan et al., 2005).

4. Results and discussions

4.1. The applicability of remote sensing in mangrove type mapping

Ten features were chosen according to CFS, including Mean Green, Mean Red, Mean NIR, Mean distance to the river, Mean DEM, Standard deviation of Green band, Standard deviation of Red band, GLCM homogeneity of NIR band, GLCM homogeneity of MIR band, and GLCM mean Red band.

Mangrove association classification by using SPOT 4 and 5, OBIA and SVM in this research had an overall accuracy (OA) of 71.9% and 81.6% in the years 2000 and 2011 respectively. Other indices (UA, PA or Mean_{SIM_Size}) across the mangrove associations also showed a lower accuracy in mangrove classification in the year 2000 compared to 2011, but the differences were minor (Table 2).

The lower classification accuracy for the year 2000 mostly caused

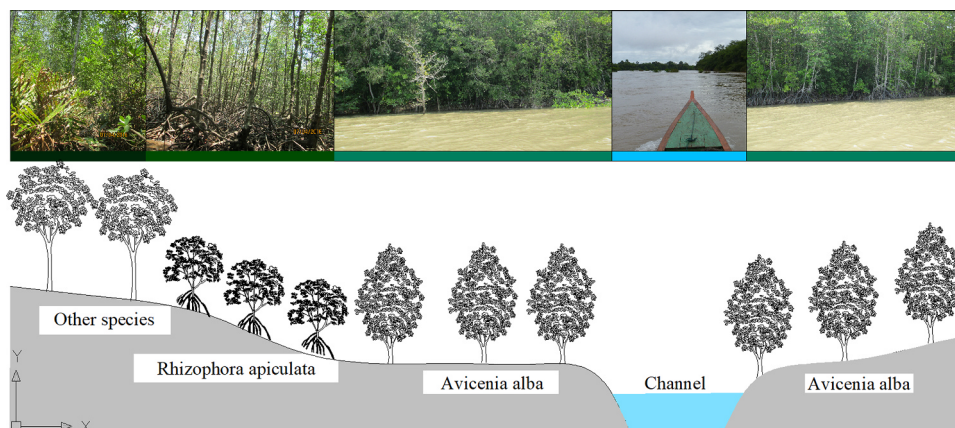


Fig. 3. Spatial distribution of different mangrove associations in Can Gio.

Table 1
Variables were used for classification.

Categories	Object's feature variables	Number of features
Spectral (Input layers: GREEN, RED, NIR, MIR)	● Mean of each layer ● Standard deviation of each layer ● Texture variables of each layer: GLCM mean, GLCM standard deviation, GLCM correlation, GLCM homogeneity, GLCM contrast, GLCM dissimilarity, GLCM entropy, GLDV mean, GLDV contrast, GLDV entropy	48
Topographic data	● DEM ● Slope ● Aspect ● Distance to the river	4

by Association III was the mixed species which could be easily mismatched with other associations. Mangrove association maps of Can Gio are illustrated in Fig. 4, and Table 2 shows the classification accuracy indices. This study showed a higher performance in mangrove classification compared to other studies such as Wang et al. (2004), which may be a result of a larger amount of features used for training in this study.

While most of the previous studies relating to mangrove mapping generally focused on the differentiation of mangrove and non-mangrove, our study focused on mangrove associations (Kirui et al., 2013; Son et al., 2015). The classification results of Association II seem to have the highest accuracy because of the homogeneity resulting from the plantation processes. Associations I and III, which often naturally expand, tend to be heterogeneity and have the lower accuracies. The accuracy of classification results from this study demonstrated the suitability of using OBIA for mangrove mapping, especially in a complex landscape such as the Can Gio biosphere reserve.

4.2. Changes in land use in Can Gio and possible consequences

There were different trends of changes of the three mangrove associations. While only Association II (*Rhizophora apiculata*) exhibited an increase of 3459 ha, Association I (*Avicennia alba* – *Sonneratia alba*) reduced around 2340 ha and Association III - mixed species decreased by 1079 ha, equivalent to 20.1% and 5.8% respectively. However, the area losses of Associations I and III were compensated by the increase of Association II (*Rhizophora apiculata*). Consequently, the total area of the mangrove forest increased slightly by only 0.1% between 2000 and 2011.

The increase in the area of Association II can be explained by the forest plantation of the Management Board of Can Gio. Since Can Gio became a biosphere reserve in 2000, the administration right was given to a local management board (McNally et al., 2011). The local government then solved the nexus between economic utilisation and mangrove forest protection for local people by re-allocating mangrove forests to local households with a tenure of 30 years. After that, they implemented rehabilitated mangrove forest projects which helped to

flourish biodiversity, especially Association II. This result was in line with McNally et al. (2011). However, the increase of Association II could cause the risk of collapsing due to strong winds because the trees were in similar sizes and ages, and this is opposite with the recommendation in Tuan and Kuenzer (2012b). Regarding Associations I and III, the decreasing trend could originate from the conversion of mangrove forests to shrimp ponds and coastal erosions caused by waves from large cargo ships, especially in the Southern and Western regions of Can Gio. We found that 1619.9 and 1481.4 ha of Associations I and III were replaced by water surfaces, respectively.

There was an inconsistent change in spatial distribution of Association I. We observed a decrease of Association I area in the North-East part of Can Gio while in the Southern part there was an increasing trend (Fig. 4). This may be caused by some reasons. The soil accretion in the Southern part may help to develop this type of mangrove, while there was a transformation in land use in the North-East parts (Pham and Brabyn, 2017). Summary statistics of the mangrove cover types in the year 2000 and 2011 are tabulated in Table 3.

We also observed an increase in the total water area by around 2655 ha and an opposite trend in other types of land use by 2736 ha. The areas of water surface included shrimp ponds (2.773 ha and 5.516 ha in 2000 and 2011, respectively) and rivers while other land cover types were bare land, road and mudflats. There were several possible reasons for these changes. Firstly, this may be due to the semi-diurnal tides of the Vietnamese East Sea. Tidal regimes fluctuate between 2 and 4 m in amplitude reported in Dang et al. (2016) which is dependent on the distance to the sea (Fig. 5). Nevertheless, as mentioned above we employed OBIA which already removed noise caused by small water pixels. Additionally, these two SPOT images were captured at the same time (10:40 a.m. and 10:43 a.m.) so the difference caused by tide was eliminated. Therefore, this extension of water surface might be due to the deforestation of mangrove forests for the development of shrimp ponds. An interview with 289 households conducted in November 2011 and reported in Kuenzer and Tuan (2013) could confirm this hypothesis since over 20% of the forest area was used for shrimp farms. The aquaculture areas tended to expand to the West and North regions of the mangrove forest, but the total area of the

Table 2
Confusion matrix of classification accuracies in 2000 and 2011.

2000					2011				
Class	Reference data				Class	Reference data			
	MG1	MG2	MG3	UA (%)		MG1	MG2	MG3	UA (%)
MG1	51	1	18	72.8	MG1	84	8	15	78.5
MG2	1	59	10	84.3	MG2	9	93	5	86.9
MG3	21	8	41	58.5	MG3	14	8	85	79.4
PA (%)	69.8	86.8	59.4		PA (%)	78.5	85.3	81.0	
OA (%)	71.9				OA (%)	81.6			
Mean _{SIM_size}	60.1	79.7	57.9		Mean _{SIM_size}	67.6	81.5	64.2	

Class key: MG1: *Avicennia alba* – *Sonneratia alba*; MG2: *Rhizophora apiculata*; MG3: mixed species.

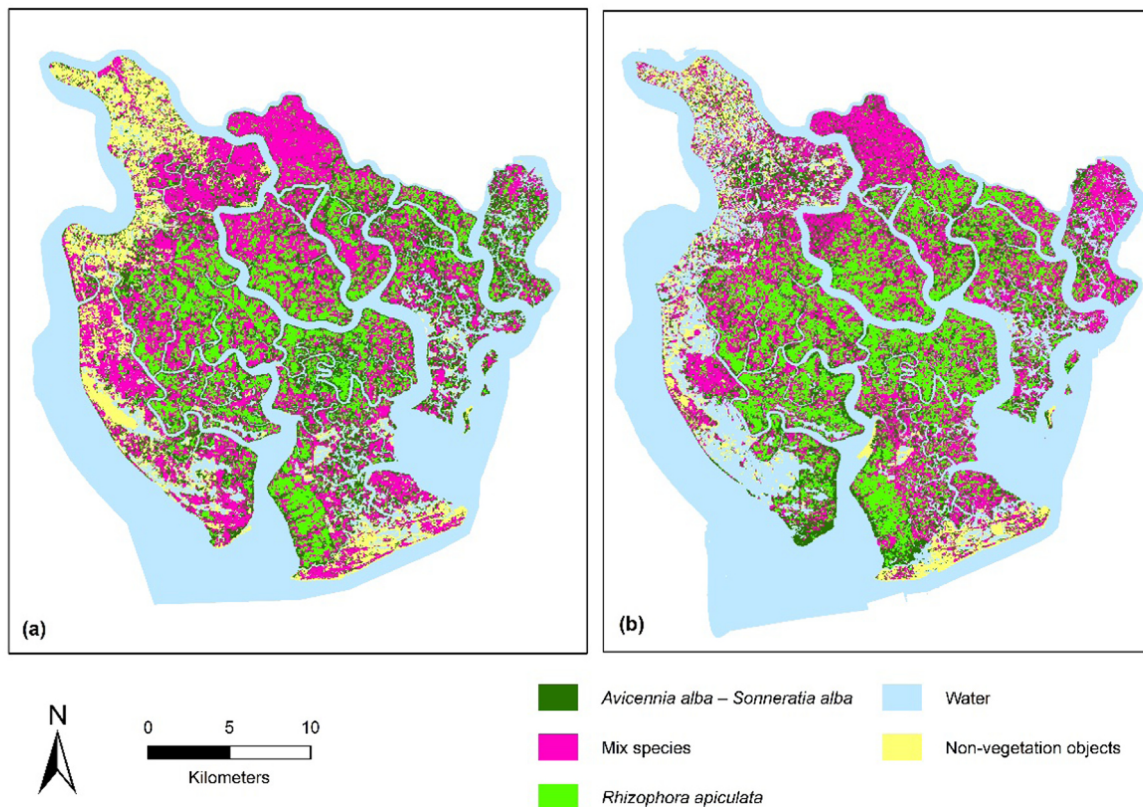


Fig. 4. Mangrove classification maps of Can Gio in 2000 (a) and 2011 (b) using OBIA and SVM.

Table 3

General descriptive statistics of areas of each type of land use in Can Gio in 2000 and 2011.

	Year 2000	Year 2011	Change
<i>Vegetation type</i>	<i>Area (ha)</i>	<i>Area (ha)</i>	<i>Total area(ha)</i>
Association I	11,625.89	9286.36	−2339.53
Association II	9916.65	13,375.76	3459.11
Association III	18,490.2	17,411.4	−1078.8
All associations	40,032.8	40,073.5	40.8
Water	30,490.8	33,145.4	2654.6
Others	6937.9	4201.8	−2736.2

forest remained so it could be concluded that the area of other kinds of land uses was reduced because of the rehabilitation of mangrove forests.

The reduction of mangrove forests and expansion of aquaculture surface along the coast and rivers, however, could result in more coastal erosion in the future. The system root of mangrove reduces the speed of currents which lead to sediment deposition so soils become more fertile and forests can be expanded (Krauss et al., 2014). When mangrove is removed due to deforestation, the soil loses its fabrication and can be easily eroded under the kinetic energy of rainfall or tidal dynamics. This phenomenon could increase vulnerabilities including the loss of lands since this region was reported to be easily susceptible to sea level rise (Dang et al., 2018a). In the case of the Can Gio mangrove forest, unfortunately, although there were no significant changes between the years 2000 and 2011 (Table 1), the reduction in forest areas mostly occurred along the estuarine and coastal regions (Fig. 4). While HCMC is one of the most exposed cities to coastal flooding due to tidal dynamics (Hanson et al., 2011) and the mangrove forest is playing a pivotal role in buffering the effect of climate change and is considered as a ‘green lung’ of the city, policy revision is needed to keep mangrove forests along the coast. What is more, the removal of Association I,

which is usually dominant in the coastal and riverine areas, however, may threaten ecological systems in the coastal and estuarine region. The disappearance of mangrove forests which provides habitats and food for living land and aquatic organisms and animals (as illustrated in Fig. 5) then threatens the existence of these species. Further studies on this topic are, thus, necessary.

This study, however, also contained several uncertainties. Firstly, Kautz et al. (2011) reported that gaps in mangrove canopy could be created by strong winds or lightning strikes, causing a mixed spectral signature and leading to misclassification between soil and vegetation. As a result, some small regions could be misclassified as a mixed type due to this effect. Nevertheless, we do not think this phenomenon contributed significantly to the changes in areas of mangrove as the total area of Association III reduced over time. Secondly, the distances between aquaculture ponds were sometimes smaller than the spatial resolution of SPOT (10 m) so many ponds were merged (see Fig. 6). This could be considered as a disadvantage of the object-based approach when working with mixed pixels. This drawback, however, did not influence the result of this study as our focus was large-scale classification and the mangrove associations.

5. Conclusion

This research showed the potential of using remote sensing, OBIA and SVM for mangrove association mapping with a high level of accuracy. The result of mangrove association classification can serve as an input for a wide variety of purposes such as forest monitoring and management, biomass prediction as well as diversity conservation in this region. Besides spectral and topographic data, in the future research, ancillary data such as soil conditions could be considered to improve classification accuracy further.

The development of classification and data pre-processing techniques has rapidly increased the number of combined techniques. However, each combination would generate a different level of

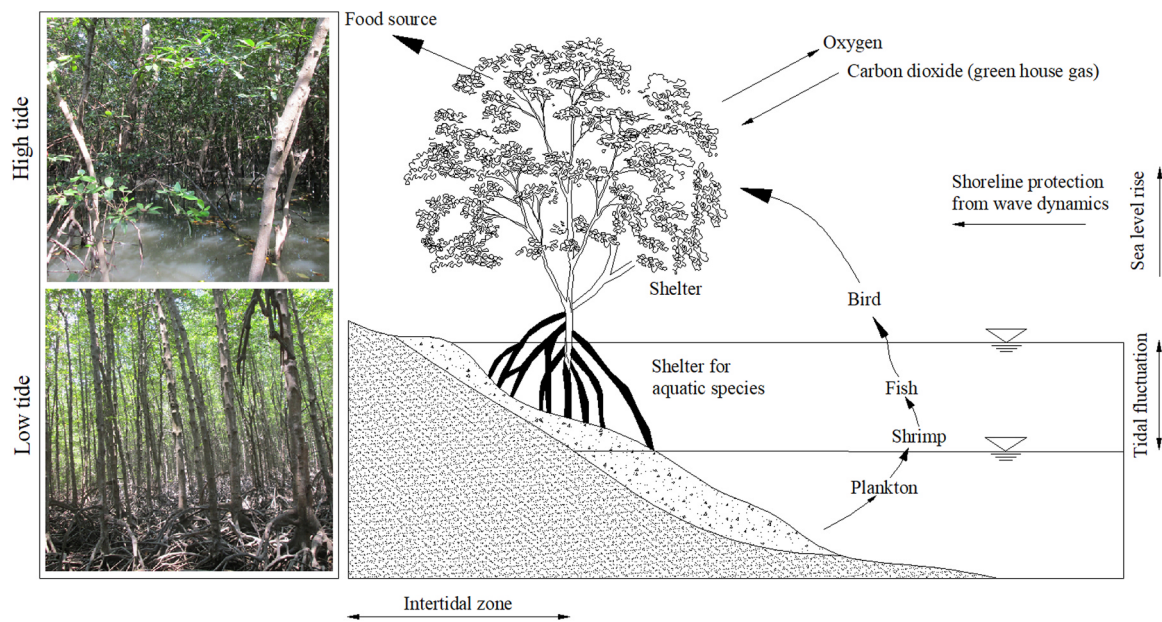


Fig. 5. Tidal impact on the Can Gio mangrove forest and the benefits of Association I (*Avicennia alba* – *Sonneratia alba*) – adapted from <http://www.deltaproof.nl>.

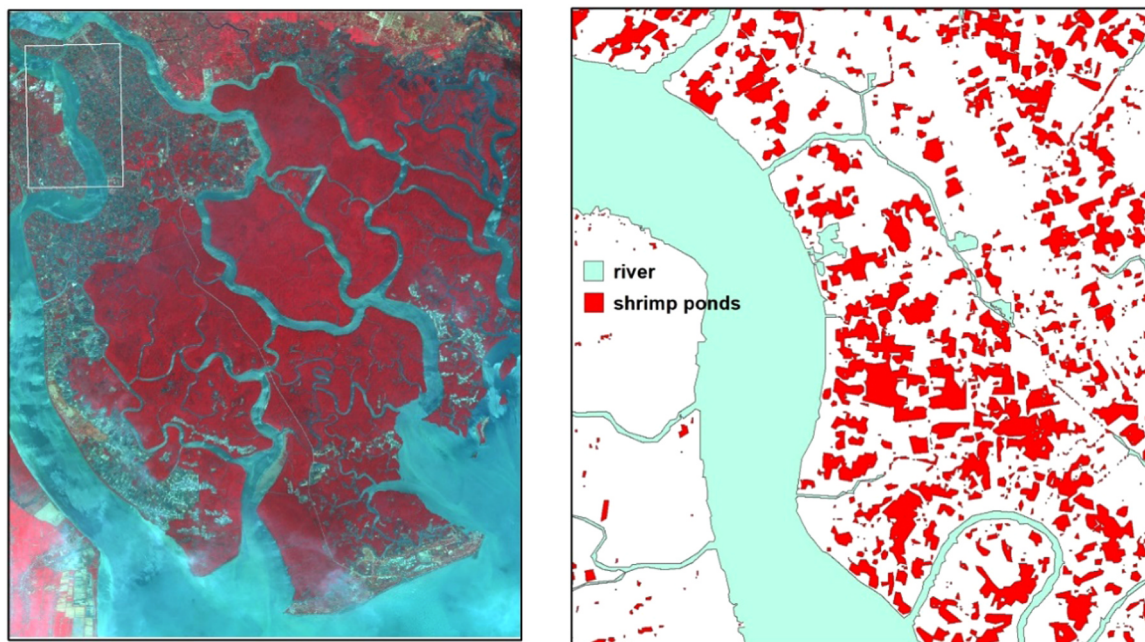


Fig. 6. Aquaculture ponds and river objects in Can Gio extracted from the SPOT imagery.

uncertainties in model output. It is important to investigate these combinations and outcomes for different applications.

The *Avicennia alba* – *Sonneratia alba* (Association I) and Association III (mixed species) areas summing up around 60% of the existing mangrove forests continued diminishing which may stimulate coastal erosion and climate change impacts. While Can Gio is a strategic region to South-East Viet Nam, especially Ho Chi Minh City, we recommend that any land use transformation and rehabilitation effort should be implemented with care to increase the diversity and capacity of mangrove to endure natural hazards. The transformation of land use from mangrove to aquaculture also contributed to mangrove deforestation to some extent. This practice may then result in coastal erosion, which then requires future expensive remediation efforts. Morphological modelling efforts and ecological studies, thus, are necessary to guide master plans.

This study did not analyse in details other land cover types that was potential for developing mangroves such as mudflats areas. These land-cover types were dynamic as they could be increasing each year due to accretion. Therefore, further research can investigate the applicability of using remote sensing and GIS techniques for providing information about intertidal mudflats suitable for mangrove plantations.

Acknowledgement

We would like to thank the Can Gio Mangrove Protection Forest Management Board for their helps in the field trips. We are also grateful to Phan Van Trung for his assistance in field works. Lien would like to thank the New Zealand Aid Programme for providing financial assistance to pursue this research.

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